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Better management zoning with elevation than with three soil classifications in a periodically waterlogged plot

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ABSTRACT

Following a comparison of the practical applicability of USDA Soil Taxonomy (ST), Hungarian soil classification (HU), and WRB in a slightly saline alluvial plot (Tóth et al., 2021), in this study, we compared the polygon alignment derived from the three systems, relative to the pattern of elevation and mean NDVI. The final objective focused on delineating potential management zones. The study plot is the largest salt-affected plot in the country (0.9 km^2). Within this plot, 85 undisturbed, 1 m deep profiles were collected, sampled, described and classified using a 100 × 100 m grid. We described the polygon alignment qualitatively and through the use of landscape metrics. Additionally, we evaluated number of classes and polygons, and delineated potential management zones based on environmental variables.

Large dominant polygons were found at level 1, the least detailed of all three classifications. The polygons became increasingly fragmented at levels 2, 3 and 4, where isolated single raster cell polygons dominated the plot in each classification: 96 % in WRB, 73 % in HU and 70 % in ST, compared to the total number of polygons. Landscape metrics proved that ST exhibited the best north–south orientation (the orientation of highs/lows), length, perimeter, area, aggregation and interspersion/juxtaposition of polygons. HU showed an intermediate performance, while WRB had the least satisfactory alignment with the north–south orientation, length, perimeter and area, as well as patch cohesion and aggregation of polygons. After analyzing the scatterplot of elevation versus mean NDVI, and also elevation versus long-term NDVI range, we noted a cutpoint of 95.47 m, which separated the more productive and less variable zone from the lower lying less productive less certain zone, given its periodical precipitation-related waterlogging.

1. Introduction

Soils are characterized by their diversity, the causes and characteristics of which have been studied in soil science from the outset (Ibáñez and Bockheim, 2013). The representation of this diversity, in essence, is the production of soil maps, which provide a theoretical and practical basis for long-term decisions. This constitutes a major task in practical soil science for applications in agriculture, forestry, ecology, environmental protection, and other disciplines (McBratney and Minasny, 2007).

The number, extent, and location of soil polygons are therefore not irrelevant. The geometric properties of soil polygons have been studied systematically by Fridland and his followers (Fridland, 1974, 1976a and b; Goryachkin, 2005; Romanova et al., 2011), with a particular focus on the "soil cover-pattern," which is the "general form of spatial distribution of the soil" (Fridland, 1976b). A recent approach utilizes landscape metrics to interpret soil polygons (Borgogno-Mondino et al., 2015; da Silva et al., 2015; Pindral et al., 2020), and has proven to be useful at

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several spatial scales (Qiu et al., 2016; Pan et al., 2019). Nevertheless, only a few publications have systematically compared the alignment of soil polygons between different classification levels and systems (see Dobers et al., 2010), which is the aim of this study.

We also recommend delineating the management zones within the study plot. The delimitation of soil polygons was initially conducted locally according to the needs of farming—as reflected in the continued widespread use of soil series in several countries (Eswaran et al., 2002). It was only a hundred or so years ago, as soil science developed and became institutionalized; that first schematic and then more and more detailed soil classifications became widespread - originally motivated by mortgage calculations, taxation and similar financial reasons. It, therefore, comes as no surprise that the founder of German soil science, Friedrich Albert Fallou, became a land value tax assessor after originally practicing as a lawyer (Feller et al., 2022). Since then, soil knowledge, utilized to support financial decisions, has evolved into an independent soil science, with hierarchical soil classification systems spanning all levels and most often upwardly aligned (Krasilnikov et al., 2009, p. 19), following the overall logic of the system. In Hungary, the old logic—from soil evaluation toward soil classification—has been turned upside down. Here, only after the development of the soil classification system (Szabolcs, 1966) was the last detailed (1:10,000) national soil map produced, and the last update of the soil classification system (Jassó et al., 1989) compiled for the purpose of land evaluation (Fórizs et al., 1971) for supporting scientifically based tax levies (e.g., the agroecological significance of the soil classes was subsequently verified). Soon after, the national land tax, the original justification for the detailed survey, was abolished in Hungary, and even its local application has since been banned (Law LVIII of 2023, 2023), though related legislation often changes from time to time.

Nowadays, the importance of detailed soil mapping and classification systems has become essential due to the need for material- and energy-efficient, environmentally friendly, site-specific management (Franzen et al., 2002; Corwin, 2013). However, operators do not often use soil classification maps, but utilize newly collected data, such as electrical conductivity (EC), elevation, and NDVI maps (Taylor et al., 2007), or combine soil maps with new data (Miao et al., 2018). This is particularly prevalent in saline soils, where there are few but well-defined and measurable, often-correlated degradation factors, such as salinity, sodicity, and alkalinity, but also technological delays due to inland water and difficult tillage, thus leading to yield losses (Johnson et al., 2003; Li et al., 2007). Some authors criticize the usability of polygons delimited by soil classification and prefer to recommend zones produced by topography and EC for farming (Fraisse et al., 2001), while others suggest that the farmer should supplement the soil map information with other data (remote sensing, crop data, topography, EC) and expert knowledge and experience to delineate zones (Mount, 1999).

We also share the conviction that the information contained in soil classification and the derived spatial representation can complement the other measured soil data in a useful way. Further, it is yet to be argued that soil polygon classification alone is sufficient to inform decisions. In Hungary, genetic soil maps have always been only one element in the decision-making process. In the most recent land evaluation (Fórizs et al., 1971), for example, the genetic base (soil type) maps were supplemented by cartograms showing various soil variation characteristics, and the "soil value" calculated on the basis of these was then corrected by the various environmental variables. In the case of on-farm soil mapping, the genetic soil type maps were supplemented with descriptive maps of other measured data and advisory maps showing the spatial potential of possible interventions. The farm agronomists did not base their decisions on genetic soil type maps for nutrient amendment, soil improvement, or land use, but on the cartograms based on the genetic soil maps.

To omit soil classification information entirely would be a significant oversight. Unfortunately, at present, even where detailed soil type maps exist, they are rarely used as a basis for management. It appears that the spatial representation of soil classifications, the soil type map, is not sufficiently used, which thus poses the question: is soil classification and soil type mapping as a practical discipline losing ground at the spatial level of real management decisions, within the plot?

It is well known to soil scientists that there is not yet an agreement on a single international classification of soils to be used universally (Langohr, 2002), such as in mathematics, physics, chemistry, biology, mineralogy, etc. In addition to the numerous official national systems, there are also two international soil classifications. The US uses and disseminates Soil Taxonomy (Soil Survey Staff, 2014) due to its size, intellectual properties, and other potential applications, and it is used in an additional 88 countries as the exclusive system (USDA, 2024), in competition with the recently developed World Reference Base of Soil Resources (WRB and IUSS Working Group, 2015), disseminated by the FAO, and now also by the European Union (Mantel et al., 2023). The comparative evaluation of the two international classification systems is a popular topic (Esfandiarpour-Borujeni et al., 2018; Sorokin et al., 2021), and the competition between the two classifications is going on before our eyes, with their spheres of influence well-defined. The slope leans toward USDA Soil Taxonomy (ST) as its regularly renewed classification does not affect the soil series depicted on the detailed maps used for farming/land use. Therefore, regular alterations and upgrades to the ST soil classification does not impact the validity of decisions based on these maps. The soil series introduced, mapped, and maintained by soil managers in the USA, Canada, UK, India, Pakistan, Malaysia, etc., are still in use (correlation tables for Puerto Rico are presented in Table 8 on page 27 of Benítez, 1983, and for Cuba in Hernández, 2006). The same cannot be said for users of the WRB, because if the detailed spatial classification is based on WRB, then changes in the classification system that occur regularly, or even frequently, will quickly render the previous maps obsolete. If a national classification is changed to WRB, the same can be said." But in the countries where the system of soil series is not in use, the users have to use the same scientific classification terms. Any change of terms leads to changes in large-scale maps and all attendant documentation." (Krasilnikov et al., 2009). The level of classification most affected by the changes is the most detailed: the level of the farm unit (parcel), where the delimitation has a specific economic dimension. For this reason, it is understandable that, where available, users of the classification stick to the established national soil classification and prefer to refine/renew the old one, rather than introduce a new system (Novák et al., 2024).

We investigated the polygons of separate soil classes in a raster arrangement based on the grid points of three soil classifications (USDA Soil Taxonomy - ST, Hungarian Soil Classification - HU, World Reference Base of Soil Resources - WRB) defined within an agricultural plot of nearly one square kilometer. In the previous publications, the differences between the three classification systems (Tóth et al., 2021), the profile sequences, the relevant properties of each profile (Tóth et al., 2022), and the spatial evaluation of salinity, sodicity, and alkalinity (Hateffard et al., 2022) were all described.

Thus far, we have shown that the classifications differ significantly on the basis of the parameters studied. At the most detailed levels, WRB surpassed HU, and ST in terms of the important homogeneity of classes (taxa). HU performed better in terms of class separability than WRB or ST. Correlation to biomass was closest in HU and WRB, yet very weak in ST. Parsimony of classes was best in ST, less in HU, and worse in WRB. With a high number of possible classification units, WRB categorized the soil into a large number of classes (Tóth et al., 2021).

As in the previous communication, in this study, we also compared the soil polygons with two factors: elevation, the most important soil-forming factor in the area, and the 10-year average NDVI as a proxy for soil productivity. Therefore, we evaluated the polygons of four classification levels in the three classifications and compared them to artificially created polygons of surface elevation and NDVI.

The following hypotheses were formulated:

The shape and spatial pattern of the soil polygons optimally follows the spatial pattern of the most important soil forming factor within the area, surface elevation, which was compared based on the quantified values of the following variables:

i. the average orientation of the polygons (i.e., the deviation from north, measured by azimuth);
ii. the average length of the polygons;
iii. the adjacency of polygons based on the Interspersion and Juxtaposition Index (IJI), Aggregation Index (AI), and Patch Cohesion Index (COH); and.
iv. the size distribution of polygons (i.e., their average size) (Fig. 1).

Based on preliminary studies, it was expected that an increasing number of classes would result in an increasing number of soil polygons within the area. With an increasing number of single-profile classes, an increased number of isolated single raster cell polygons were expected. We expected to find a correspondence between the spatial pattern of environmental variables (elevation, NDVI) and the pattern of mapping units. A higher correspondence with the polygon geometry of elevation and NDVI was expected with HU and WRB than with ST.

In this study, we compared the spatial patch pattern by considering the four levels of the three soil classifications and evaluated taxonomically homogeneous polygons. Each profile was classified independently on its own, without the intention of spatial or categorical generalization. However, for the more detailed levels of classification, during mapping, some classes are grouped together on soil maps (e.g., consociations, complexes and associations, undifferentiated groups [Soil Survey Staff, 1993]), and the demonstration and evaluation of this was not the subject of our study.

2. Materials and methods

In this study, the arable plot, used mainly for growing cereals (see Fig. 1 of Hateffard et al., 2022), is located on the outskirts of the village of Dunavecse, Central Hungary, on the former floodplain of the Danube River. The soils are slightly saline and have a sandy-loamy texture, with increasing average particle size along the depth of the profile. The water table is shallow and saline. Local depressions, formerly densely vegetated, are characterized by a higher fraction of silt, organic matter, and salt content, and a lower concentration of carbonates. Elevation dominates most soil properties, as shown in Table 4 (McBratney et al., 2000) and recently documented by Vacek et al. (2020). At increasing elevations, the mean salt concentration, pH, sodicity, clay content, and organic carbon content decreases, as well as an increase in $CaCO_3$ content is seen at a depth ranging from 0 to 100 cm. The climate is subhumid continental with a mean annual temperature of about 10.5 °C.

All field observations, measurements, and the sampling scheme were described by Tóth et al. (2021, 2022), and Pásztor et al. (2023). In summary, there were a total of 85 profiles at the center of 100 × 100 m grid cells, but due to the irregularity of the plot, four in a relative proximity. One-meter deep undisturbed tube profiles were collected in the field and were subsequently analyzed and classified; all related information is shown in Tóth et al. (2022).

A raster sampling scheme was introduced for facilitating the use of landscape index calculations. We worked with polygons, i.e., contiguous raster cells of the same soil class (taxon) using queen adjacency. Our approach was different from the traditional mapping, in that we did not focus on smooth boundaries between classes and did not combine soil classes with elevation, or other factors. In order to adopt raster evaluation, the continuous elevation and NDVI variables at the bore points also had to be categorized. To obtain a reasonable comparison of the polygon properties, the elevation and NDVI class numbers were defined as the average of the class numbers of the three soil classifications, such as at Level 1 (top), 4 classes; Level 2, 10 classes; Level 3, 23 classes; and at the most detailed level, Level 4, 34 classes. The lower and higher threshold values of the classes of elevation and NDVI were determined using one-dimensional K-means clustering from the most detailed classes by ensuring that the four classification levels comprise a strictly hierarchical, inclusive classification of these variables.

Landscape metrics, the interspersion and juxtaposition index (IJI), aggregation index (AI), and patch cohesion (COH) were determined to reveal the spatial pattern of the heterogeneity of soil polygons. IJI expresses the degree of aggregation based on the adjacency of polygons; the higher the value, the higher is the dispersion of polygons. The COH index is proportional to the area-weighted perimeter (i.e., area ratio divided by area-weighted mean shape index); thus, increasing the value means increasing cohesion. AI is the ratio of actual edges to the total amount of possible edges, with 0 indicating complete disaggregation and 100 meaning complete aggregation (McGarigal et al., 2023). Landscape metrics calculations were based on the maps (raster cells) of the different soil taxonomy systems at different levels. Altogether, we performed 12 analyzes for three taxonomy systems (HU, ST, and WRB) for classification levels 1 to 4. Longest straight lines' azimuth and length were determined in QGIS using Python programming. All calculations were performed in R.4.3.2 (R Core Team) with the landscape metrics package (Hesselbarth et al., 2019).

One-way ANOVA was used to compare the mean values of the following parameters: azimuth, length, perimeter, area, AI, COH, IJI. Significant pairwise differences between the classifications were listed in the figure captions.

To delineate the management zones, the 10-year mean NDVI versus elevation, and NDVI range versus elevation scatterplots were visually interpreted to find a cutpoint, which was validated by the analysis of the histograms of the two NDVI-related variables.

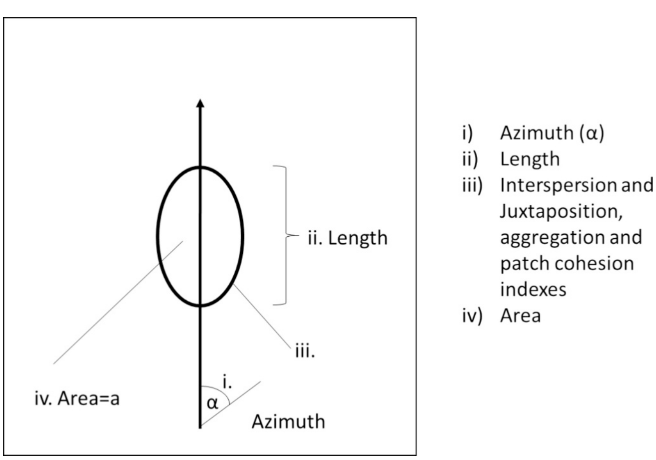

Fig. 1. The polygon parameters investigated in this study.

3. Results and discussion

3.1. Polygon alignment of the three classification systems at four levels

3.1.1. Soil Taxonomy

3.1.1.1. Level 1—Suborder. Each order was represented only by one suborder; therefore, the polygons of the two levels—order and suborder—were the same. At level 1, the plot was dominated by one large contiguous polygon from the Ustolls suborder, indicating the north–south orientation (Supplementary Fig. 1).

The second most extensive suborder was Ustepts, forming four polygons close to the three edges of the large Ustolls polygon, with a tendency toward northeast–southwest-oriented polygons whenever the polygons were more than two raster cells in size. The Orthents suborder was represented by one isolated single raster cell polygon.

3.1.1.2. Level 2–Great group. The overall north–south orientation of polygons with a minor southwest–northeast tendency was maintained at this level (Fig. 2). Semi-continuous ridges of Haplustolls were observed, whereas areas of lower elevation were dominated by Calciustolls, indicating the effect of a shallow water table, as reported by Abtahi and Khormali (2001).

Inceptisols polygons, which showed no further spatial fragmentation as compared to level 1, were separated due to the occurrence of Calciustepts at the southern and Haplustepts at the northern edge of the plot.

3.1.1.3. Level 3–Subgroup. There was a weak tendency toward a north–south orientation of polygons at this level (Supplementary Fig. 2). Udic Calciustolls were predominantly, but not solely observed at lower elevations. Areas of higher elevation, however, presented a more fragmented pattern with a somewhat poor correlation, with a dominance of Udic Haplustolls. However, in the north–central area and the western edge of the study plot, Udic Haplustolls were found at local depressions. Isolated single raster cells of Typic Haplusteps and Udic Calciusteps occupied areas of medium elevation in the northeastern and southern margins of the plot, respectively. Groundwater-affected Aquic Calciusteps again indicated a prevailing, fragmented pattern over the entire plot, but not exclusively in low-lying areas.

3.1.1.4. Level 4–Family. Level 4 revealed a perceivable tendency toward a north–south orientation of polygons (Supplementary Fig. 3). Sandy, mixed, mesic Udic Calciustolls were predominantly, but not solely observed at lower elevations. Level 3 categories were fragmented, and isolated single raster cells dominated the plot in the case of Ustepts and Orthents.

3.1.2. Hungarian classification

3.1.2.1. Level 1–Main soil type. At level 1, the highest-lying area was mainly dominated by one contiguous polygon of Chernozem main type, showing a north–south orientation (Supplementary Fig. 4).

The second-most extensive main type was the low-lying Meadow, forming five polygons at all edges of the large polygon of the Chernozem main type, with a tendency toward north–south oriented polygons, whenever more than three raster cells large in size. Alluvial soil main type, occurring at an intermediate elevation, was only represented by three small isolated (two out the three) polygons.

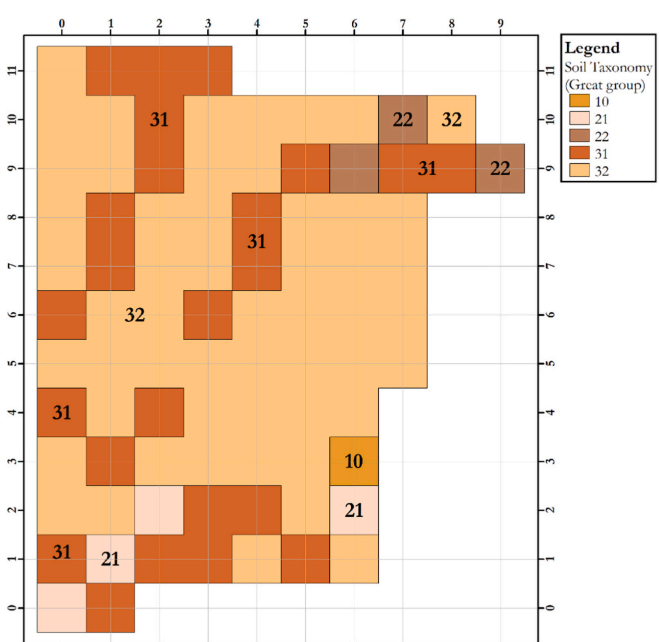

Fig. 2. Raster map of Soil Taxonomy at level 2. 10 is Ustorthents, 21 is Calciustepts, 22 is Haplustepts, 31 is Haplustolls, 32 is Calciustolls.

3.1.2.2. Level 2–Soil type. At level 2, whenever there were more than two raster cells in the polygon, the orientation was typically north–south (Supplement Fig. 5). Among the three Chernozem soil types, the “Meadow chernozem” soil type inherited the polygon alignment of the Chernozem main type, indicating the previously mentioned north–south orientation. Among the three Meadow soil types, the longer polygons showed the same orientation. The Alluvial main soil type had only one soil type, “Humous alluvial soil.” Therefore, its polygon alignment has not changed compared to level 1.

3.1.2.3. Level 3–Soil subtype. At level 3, there were many isolated single raster cells. Among the two-raster-cell polygons, five had a north–south orientation, two had an east–west orientation, and there were also several oblique polygons (Fig. 3). Among the five subtypes of Chernozem soils, although the polygons exhibited a large fragmentation, the north–south orientation was perceivable.

There were six subtypes of Meadow soils, which was a larger number than the number of Chernozem subtypes for this less extensive main type. Though fragmented, their polygons still resembled the original clear north-south alignment. The Alluvial soil type had only one subtype, and its polygon alignment was the same as at level 1 and 2.

3.1.2.4. Level 4–Soil variety. Most of the polygons were isolated single raster cells (Supplementary Fig. 6). Among the two-raster-cell polygons, four had a north–south orientation and two an east-west orientation. Predominantly comprising single raster cells, the Chernozem soil variety polygons did not demonstrate a clear orientation.

Most Meadow soil varieties formed single raster cells, but when there was more than one raster cell in the polygon, the orientation was north–south. All Alluvial soil varieties formed single raster cells.

3.1.3. World Reference Base for Soil Resources

3.1.3.1. Level 1–Reference soil group (RSG). At level 1, the dominant reference soil group was Chernozem, forming the dominant polygon of the plot. The Cambisol, Gleysol, and Regosol polygons occurred exclusively in isolated single-raster cell polygons (Fig. 4). These dispersed taxonomic units did not demonstrate a clear relationship with the elevation or NDVI pattern, as their weak correlation already demonstrated in the former study (Tóth et al., 2021).

3.1.3.2. Level 2–Reference soil group + 1 principal qualifier. At level 2, the Chernozem RSG matrix splintered into distinct, yet still larger polygons, classified as Amphicalcic, Endocalcic, Epicalcic, and Katocalcic Chernozems (Supplementary Fig. 7). Their spatial differentiation was based on the vertical position of the secondary carbonate accumulation. The Phaeozem and Calcisol reference soil group polygons observed at level 1 were fragmented according to the occurrence of gleyic and calcaric characteristics of soils, mostly occupying intermediate low-lying areas.

3.1.3.3. Level 3–Reference soil group + 2 principal qualifiers or Reference soil group + one principal and one supplementary qualifier. At this level, there was one five-raster cell-large polygon, Amphicalcic Chernozem (Endoprotosalic) (code 725); one three-raster cell-large polygon, Haplic Chernozem (Endoprotosalic) (code 713); and three polygons containing two raster cells, such as the Endogleyic Amphicalcic Chernozem (723), Calcaric Chernic Phaeozem (521), and Endocalcic Chernozem (Cambic) (743) classes, which indicated an orientation toward the north–south ridges (Supplement Fig. 8). All the other polygons were formed by

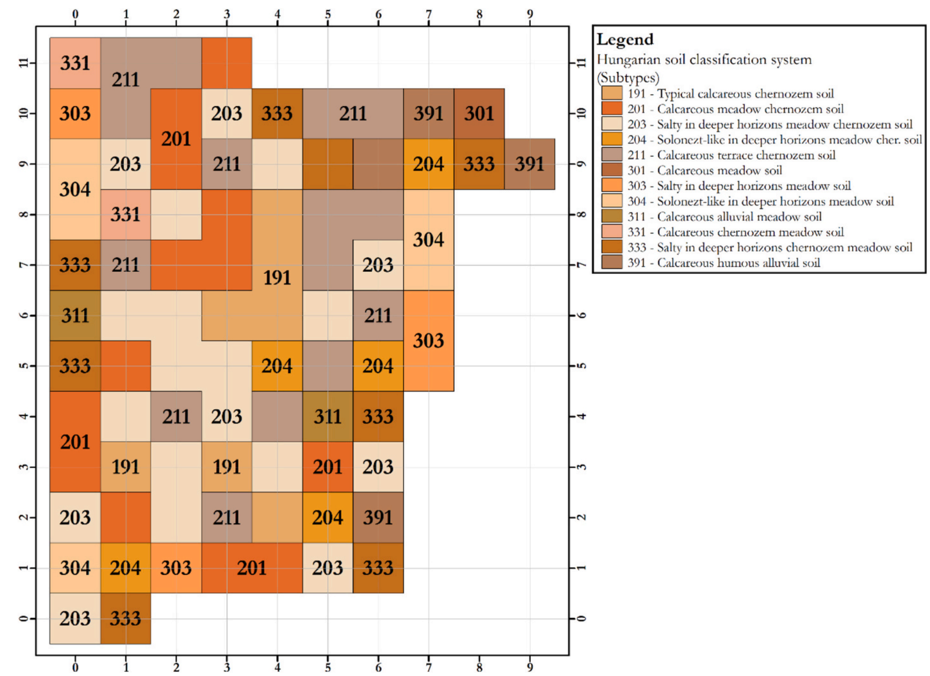

Fig. 3. Raster map depicting the Hungarian classification at level 3.

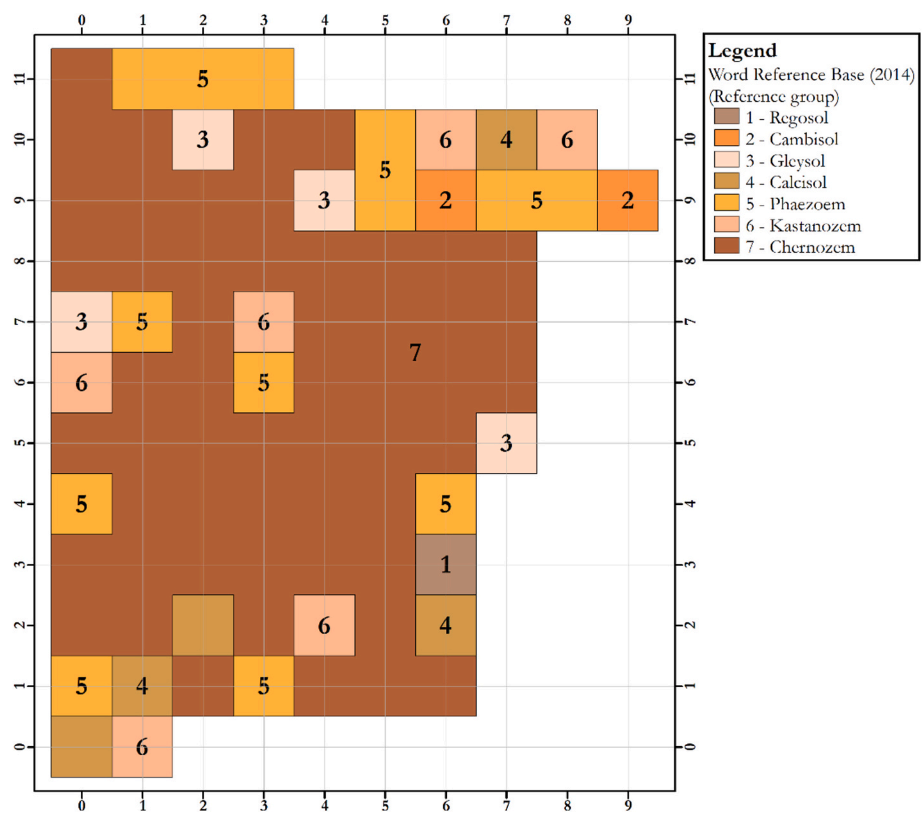

Fig. 4. Raster map showing WRB classification at level 1.

isolated single raster cells.

3.1.3.4. Level 4–Reference soil group + 3 principal qualifiers or Reference soil group + 2 principal and one supplementary qualifier or Reference soil group + 1 principal and 2 supplementary qualifiers. At this level, only three polygons were larger than one raster cell: Haplic Chernozem (Endoprotosalic) (code 7130), Amphicalcic Chernozem (Endoprotosalic) (7250), and Endocalcic Chernozem (Cambic) (7430), without demonstrating a clear orientation (Fig. 5).

With increasingly detailed classification systems, evidently, an increasing number of classes/polygons were observed. The north–south-oriented polygons were fragmented into smaller polygons, and

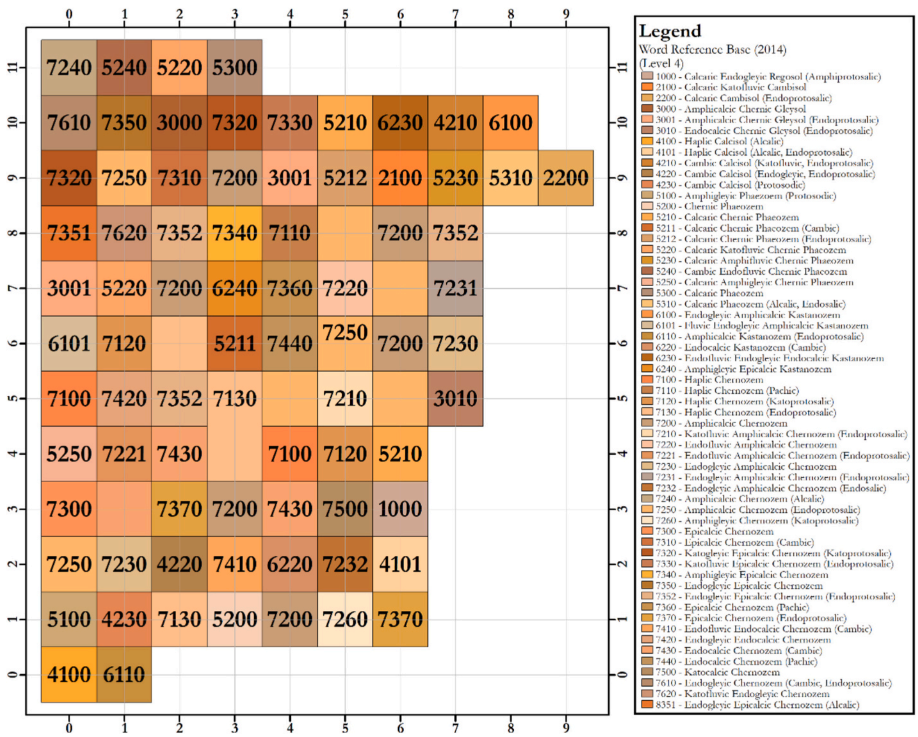

Fig. 5. Raster map depicting the WRB classification at level 4.

eventually into isolated single raster cell polygons. North–south oriented polygons were most perceivable in the case of HU, which were even detectable at level 4, and the least perceivable in the case of WRB.

All three systems provided large dominant polygons at level 1, such as Ustolls (ST), the Chernozem main type (HU), and Chernozem RSG (WRB). Following the fragmentation of the largest polygon, polygons of subclasses were discernible at all levels in the case of ST, visible at level 2 in HU, but disappeared at level 2 of WRB (except for a polygon at the eastern border of the plot). Isolated single raster cell polygons were the dominant polygon size in WRB, less in HU, and least in ST.

3.2. Number of classes and polygons among the three classification systems at four levels

Artificially fragmented polygons of the continuous background variables—elevation and NDVI—are presented in Supplementary Figs. 9 and 10 as a reference for the interpretation of the number of polygons in the three classification systems. Compared to ST and HU, the WRB classes were numerous at all levels, skewing the average number of classes (see Fig. 6) toward greater numbers and providing a similar amount of fragmentation in the two background variables to WRB.

WRB demonstrated the largest number of classes (Fig. 6) and polygons (Fig. 7), whereas ST provided the least number of both. ST and HU joined several raster cells dispersed across the artificially fragmented raster maps of elevation (Supplementary Fig. 9) and NDVI (Supplementary Fig. 10). In comparison, WRB added further fragmentation, as shown by the number of polygons at level 1, 3, and 4 (Fig. 8).

The number of isolated single raster cell polygons of WRB exceeded those of the background environmental variables and demonstrated the largest number of isolated single raster cell polygons, whereas ST provided the lowest number (Fig. 8).

With increasing amounts of classification detail, the numbers of classes and polygons were expected to increase, as illustrated in Fig. 9. The first two to three levels of the three classifications represent slowly increasing numbers of classes, after which there is a marked increase in the number of polygons representing the varied field conditions. While

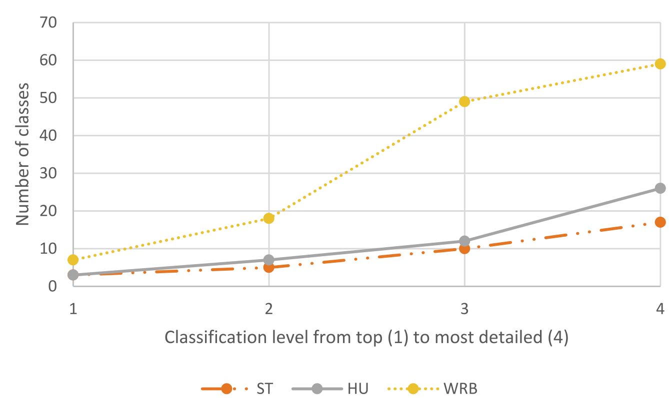

Fig. 6. Number of classes distinguished inside the plot in the three classification systems (Tóth et al., 2021). Percentage of single profile classes (based on the total number of classes) in ST: 33, 20, 40, and 41 %; in HU: 0, 0, 8, and 54 %; and 14, 33, 67, and 78 % in WRB, at classification levels 1, 2, 3, and 4, respectively.

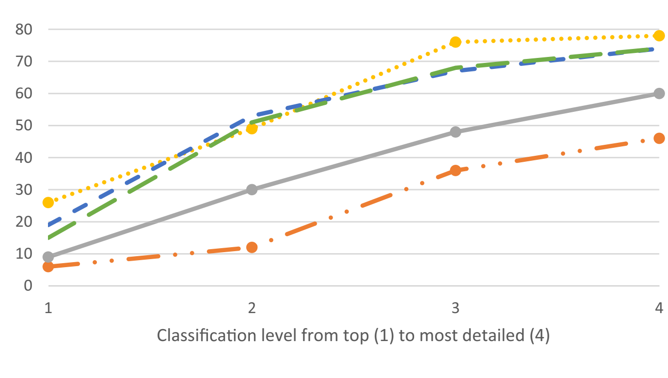

Fig. 7. Number of polygons in the three classification systems.

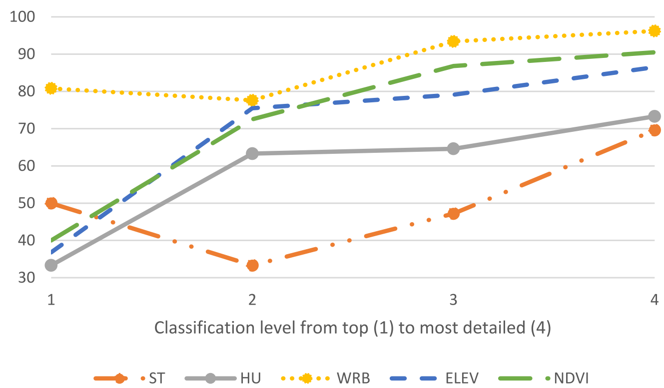

Fig. 8. Number of isolated single raster cell polygons as a percentage of total polygons in the four levels of the three classification systems.

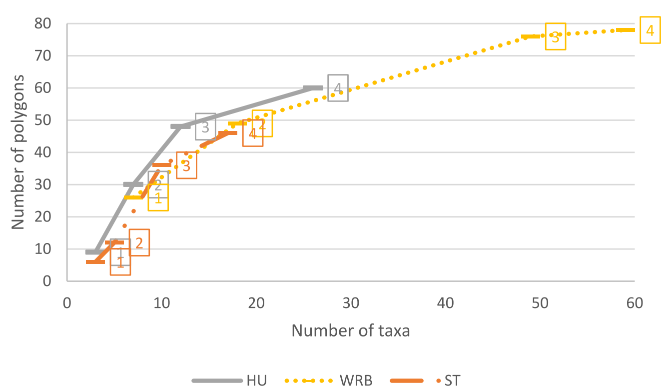

Fig. 9. Relationship between the number of classes and the number of polygons. Numbers inside the graph indicate classification level by their respective colors.

all three curves resemble initial parts of saturation curves, ST and WRB indicate an overlap, with HU showing a similar curve, thus pointing to a similar fragmentation of classes. In the case of WRB, the comprehensive, in-depth approach resulted in an extreme number of classes and polygons (Fig. 9). However, what is most problematic is the increasing number of single profile classes and related isolated single raster cell polygons, which complicates the planning of management considerably (Fraisse et al., 2001; Taylor et al., 2007).

On the other hand, as the WRB does not impose an upper limit on the number of classes, the number and precision of the soil classes that can be created through the numerous qualifiers (principal or supplementary) classifications increases continuously, and consequently becomes increasingly sensitive to soil heterogeneity. The other extreme is Soil Taxonomy, which was not sensitive to minor differences in the soil profiles, and did not show a statistically significant correlation between classes and background variables.

3.3. Comparison of the landscape metrics of polygons of the three classification systems at four levels

Mean ST azimuth values (Fig. 10) exceeded the other two classification systems by indicating a more northward orientation of polygons than the other two classification systems and the background elevation (ELEV) and NDVI variables. ST showed significant pairwise differences at all levels, and HU at level 1 and 3. WRB did not show the expected north–south orientation at level 1.

ST demonstrated longer polygons than the other two classification systems, except at level 1 (Fig. 11). ST highlighted significant pairwise differences at all levels, and HU at level 1 and 3; WRB demonstrated the shortest polygons.

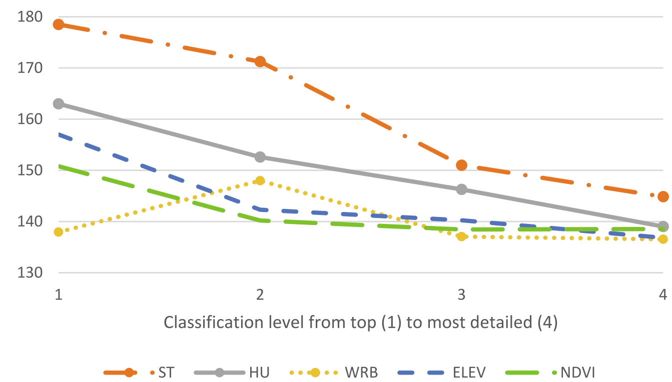

Fig. 10. Means of azimuth calculated with the classes at every classification level. There were significant differences at Level 1 between ST vs WRB, WRB vs ELEV, HU vs WRB; at Level 2 between ST vs WRB, ST vs ELEV, ST vs NDVI; at Level 3 between ST vs WRB, ST vs ELEV, ST vs NDVI, HU vs WRB; at Level 4 between ST vs WRB, ST vs ELEV, ST vs NDVI pairwise.

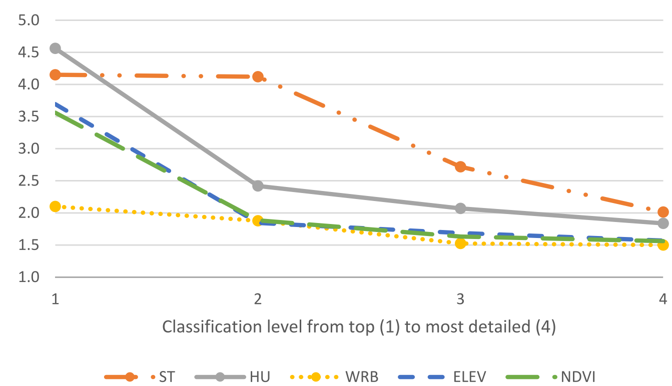

Fig. 11. Mean values of polygon length (in meters, to be multiplied by 100). There were significant differences at Level 1 between HU vs WRB; at Level 2 between ST vs all others; at Level 3 between ST vs all others, HU vs WRB, HU vs ELEV, HU vs NDVI; at Level 4 between ST vs WRB, ST vs ELEV, ST vs NDVI pairwise.

The comparative evaluation of polygon perimeter values (Supplementary Fig. 11) showed very similar results to the length values. ST exceeded the other two classification systems and showed longer perimeters than the other two classification systems, except at level 1. ST identified significant pairwise differences at levels 2, 3, and 4.

Mean ST area values exceeded the other two classification systems and showed significant pairwise differences at levels 2, 3, and 4 (Fig. 12). WRB showed the smallest polygons at every level.

IJI was evaluated for both classification levels and classes. As Fig. 13 shows, ST provided the best aggregation based on the adjacency of polygons.

Mean IJI values of all classifications (Supplementary Fig. 12) were lower than the same for ELEV and NDVI, HU approached their value at levels 3 to 4, and ST at level 4. WRB showed the lowest value at levels 3 to 4.

ST and HU showed very similar mean Aggregation Index values (Fig. 14) as compared to ELEV and NDVI, but WRB showed lower values.

ST and HU showed very similar mean Patch Cohesion Index values (Fig. 15) as compared to ELEV and NDVI, whereas WRB showed lower values. From level 2, ST demonstrated several significant pairwise differences.

We found a correlation between the background elevation and NDVI variables and the landscape metrics of each classification *en bloc*, with a few subtle differences. Soil Taxonomy excelled in the north–south

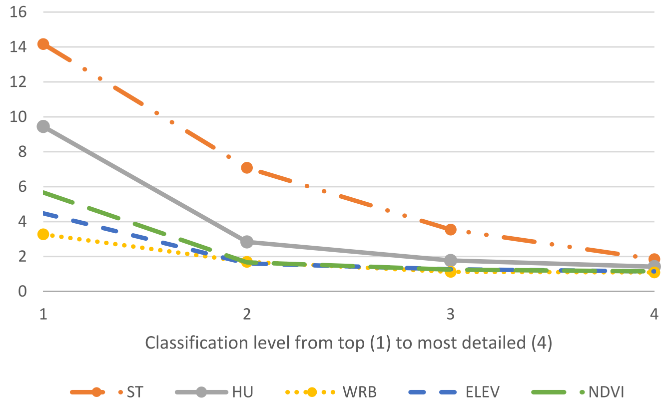

Fig. 12. Mean areas of polygons calculated for each classification. There were no significant differences at Level 1; however, at Level 2 and 3, there were significant differences between ST vs all others; at Level 4 between ST vs WRB, ST vs ELEV, ST vs NDVI pairwise.

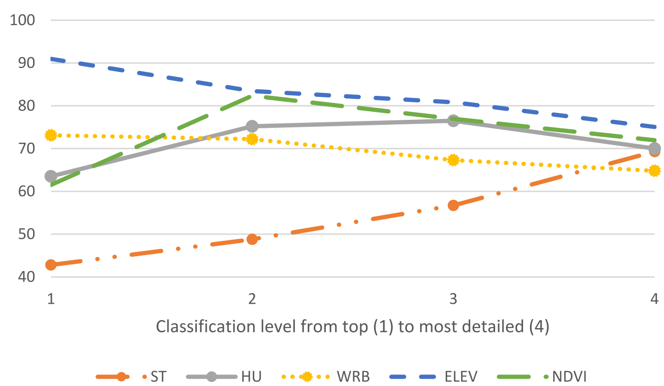

Fig. 13. Interspersion and Juxtaposition Index (%) for each classification level.

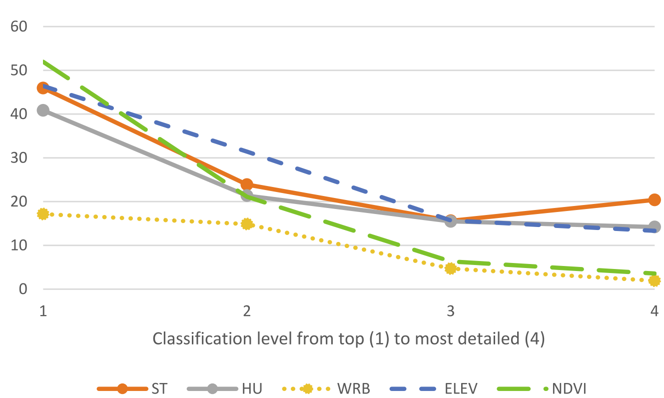

Fig. 14. Means of Aggregation Index (%) calculated with classes at every classification level. There were no significant differences between levels 1 to 3, but at Level 4, ST vs WRB and ST vs NDVI showed significantly different mean values pairwise.

orientation, length, perimeter, area, aggregation, and interspersion/juxtaposition of polygons. WRB showed the worst match with the curves of the north–south orientation, length, perimeter and area, patch cohesion, and aggregation of polygons.

The Hungarian classification performed between ST and WRB in many characteristics. While closer to ST, HU had fewer significant differences pairwise.

Regarding length, area, perimeter, and azimuth, ST had the largest values, followed by HU, and lower by ELEV and NDVI, similar to WRB.

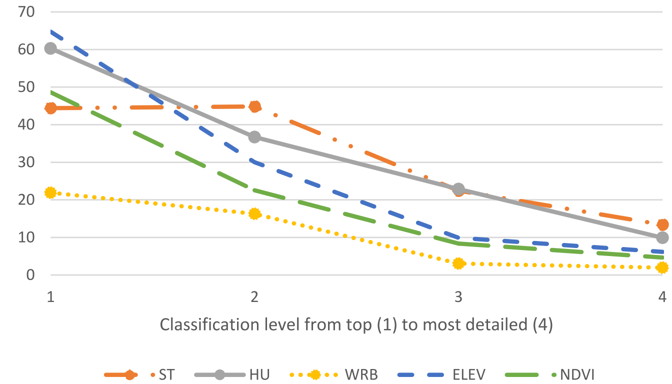

Fig. 15. Means of Patch cohesion (COH index) values (%) calculated at every classification level. There were no significant differences at Level 1; but there were at more detailed levels, namely at Level 2 between ST vs WRB; at Level 3 between ST vs WRB, ST vs ELEV, ST vs NDVI, HU vs WRB, HU vs ELEV, HU vs NDVI; at Level 4 between ST vs WRB, ST vs NDVI, HU vs WRB pairwise.

For AI and COH, ELEV and NDVI had comparable values that were larger than ST yet similar to HU, both surpassing WRB.

For IJI, ELEV and NDVI showed very similar values, similar to HU, which was larger than ST, all surpassing WRB. Pan et al. (2019) compared the relationship between classification grains and landscape metrics, with their results showing similar curves to those we achieved. In a parallel study, Qiu et al. (2016) compared two classification systems. Based on four landscape metrics, the researchers demonstrated that Chinese Soil Taxonomy is more precise than Chinese Genetic Soil Classification at a scale of 1:500,000.

3.4. Delineation of polygons (management zones) by environmental variables

Within the study plot, the three soil classifications produced different polygons, but their prediction capacity could not compete with the biomass estimate provided by the close relationship between elevation and NDVI variables. Although this could have been due to the negative correlation of elevation with soil salinity, it was more likely caused by the decreasing probability of the presence of a shallow water table with an increasing elevation. Due to the presence of shallow groundwater under the plot, soil salinity increases with decreasing surface elevations. In the case of saline soils, agronomic generic thresholds have long been used to delimit the polygons of different fertility ratings (Richards, 1954; Maas and Hoffman, 1977); however, in this plot, there was no saline ($EC_e > 4$ dS/m) topsoil, and the 4 dS/m threshold of salinity was reached in seven out of 85 one meter deep profile. Based on the relationship between background variables (Tóth et al., 2021, Section 3.3, Fig. 2), we used elevation as a continuous variable to delineate management zones with a distinct expected yield.

The size of the plot studied and the occurrence of intermittent waterlogged patches necessitate the separation of at least two types of patches: regularly waterlogged and non-waterlogged. The plot of the 10-year average NDVI values (Fig. 16) and the NDVI range (Fig. 17) can also be split into two datasets at an elevation of 95.47 m, which, given the limitations of the raster representation, roughly follows the extension of the waterlogged patches shown in Fig. 18. For the former, this limit separates two NDVI peaks (see also Supplementary Fig. 13); for the latter, above this elevation value, the NDVI range value drops abruptly (see also Supplementary Fig. 14); i.e., for the farmer, the area thus delimited shows both a high biomass, indicated by high NDVI values, and low production uncertainty, indicated by low NDVI range values.

The cutpoint resulted in the delineation shown in Fig. 19., where the classes positioned lower and higher in the chart are termed “Periodically waterlogged” and “Productive”, respectively. This map is similar to the

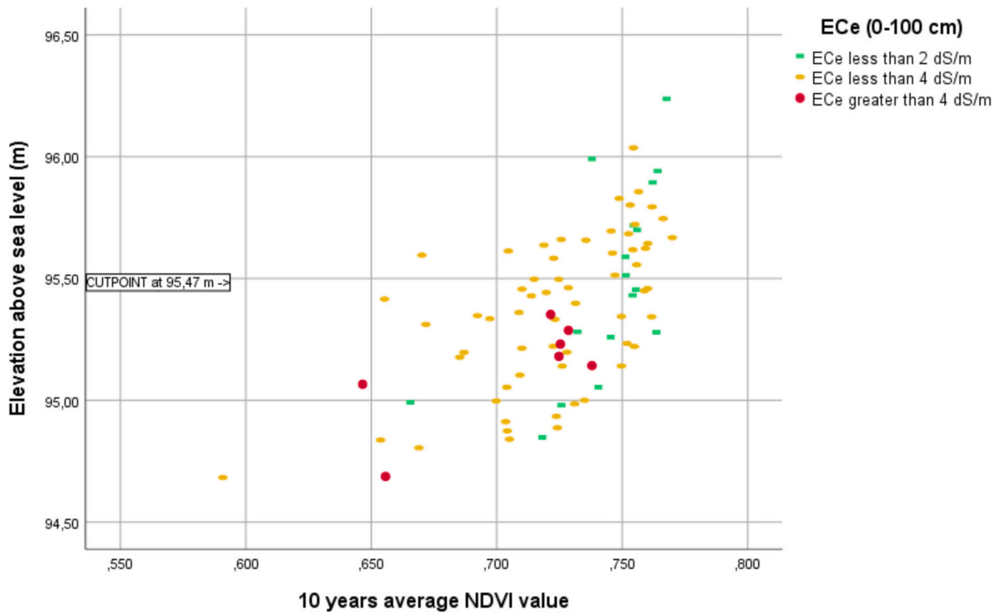

Fig. 16. Mean NDVI vs elevation. See the cutpoint of 95.47 m separating high mean NDVI values from low values.

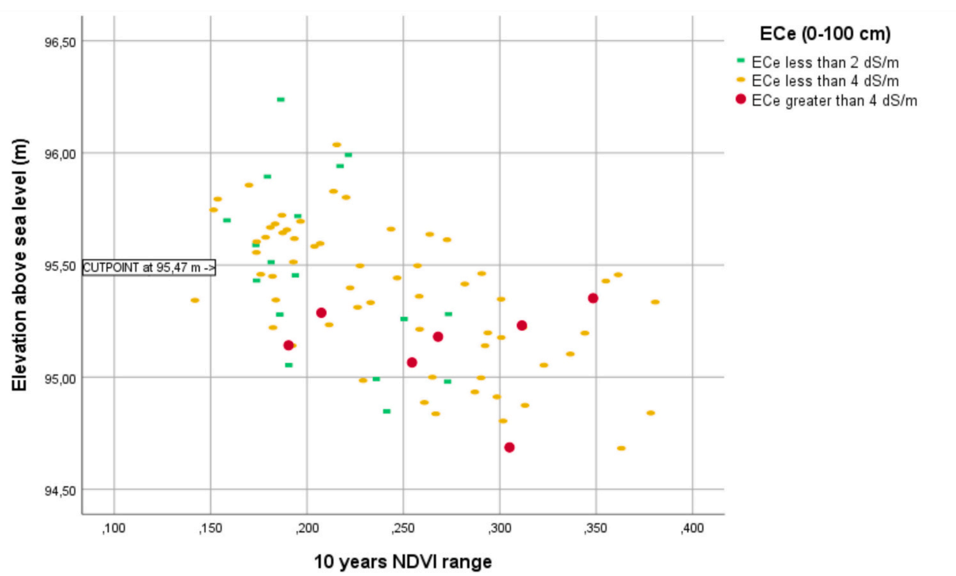

Fig. 17. NDVI range vs elevation. See the cutpoint of 95.47 m separating high NDVI range from low range.

previously shown maps of the least detailed levels of all three classifications of the study plot. In the higher lying category, two polygons were formed by isolated single raster cells, one two-cell, and one four-cell polygon. All the other polygons formed large branching polygons. A statistical test showed a significant difference in the mean values of 10-year mean NDVI values, the NDVI range, and profile average ECe values between the two classes mentioned above. This approach is very similar to that of several authors, such as Fraisse et al. (2001), who preferred the "objective classification method" to soil classification.

Using soil classes created by the classification systems would produce too many zones in this extensively cultivated grain field, except for the first level of ST (Supplementary Fig. 1) and HU (Supplementary Fig. 4) with 3–3 classes. As reported by Tóth et al. (2021) (3.3 iia and iib), due to a lack of significant differences of mean NDVI values between the classes, ST was not suitable for such delineation. The Hungarian classification provided two significantly different classes, the larger Chernozem and Meadow soil main types; however, the Alluvial soil main type did not differ from those. This superior performance of HU compared to ST was supported by the significant correlations found between elevation and NDVI for HU, and none for ST (Tóth et al., 2021, Section 3.4.3.). Our preliminary expectation was that more detailed classification levels could be optimal for delineating management zones inside one plot, such as the one found by Franzen et al. (2002) and Miao et al. (2018); however, the least detailed classes, such as level 1, could be employed in our study, similar to Dobos et al. (2023). In this plot, the zone created by periodic waterlogging and a shallow water table depth, all linked to the Meadow soil main type, caused this spatial distribution, and such a periodically repeating spatial pattern depicting the highs and lows is typical in the Pannonian Basin (Tóth et al., 2019) and elsewhere. Similar to the experience gained in Uganda (Kyebogola et al., 2020), our domestic classification system surpassed both international classification systems for delineating management zones.

Compared to the case of soil classes, the use of two elevation zones with the suggested cutpoint provides zones with significantly different

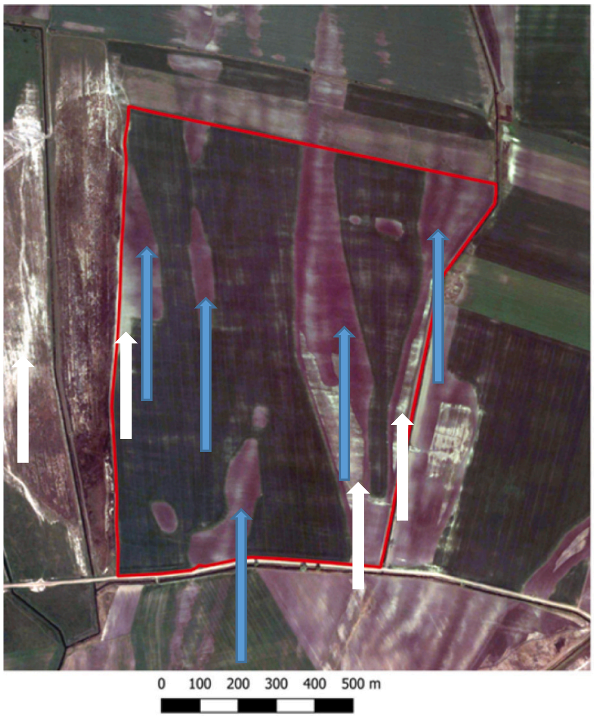

Fig. 18. Waterlogged patches observed on the study plot as shown by a satellite image downloaded from Google Earth (taken on Nov 4, 2011). Salt efflorescence patches are clearly distinguishable within the plot and in the grassland areas outside the plot. Blue arrows indicate waterlogged patches, white arrows indicate salt efflorescence patches.

mean NDVI, NDVI range and profile average ECe values of the two zones; such a prominent role of elevation is well known (Jenny, 1941, Chapter V; Franzen et al., 2002). Furthermore, the two management zones do not complicate the management of the plot (Taylor et al., 2007).

One limitation of our approach was the independent evaluation of the soil profiles without full consideration of their spatial location, which could result in potential generalized polygons from the outset in a mapping exercise. Raster cells provided an opportunity to utilize landscape metrics to interpret the polygon alignment in a straightforward manner; however, the subtle spatial pattern of background factors and soil salinity could be hidden in the raster cells. Another limitation of our raster approach could be that the 100x100m grid provides a sampling quality that is too coarse. As Fig. 18 shows, and as is typical in salt-affected areas, the distribution of saline spots does not strictly follow the elevation; therefore, several smaller patches were not sampled by the tube profiles, but their elevation and NDVI values were incorporated into the raster cells. As a result, there was a weaker correlation between background variables and soil properties than theoretically, or as would be possible with a finer grid.

4. Conclusions

Though we initially anticipated a proportionally larger number of soil polygons with an increasing number of soil classes, our findings revealed more polygons than expected, with isolated single raster cell polygons dominant at the most detailed levels of classification. Therefore, it would not be feasible to propose the construction of management zones based on the detailed classification levels alone. Contrary to our expectations, not soil classes, but the background variable of elevation, provided the best separation of potential management zones.

Based on our results, a possible recommendation would be to develop guidelines for all soil classification/mapping systems on how to utilize the different levels of soil classification information in the

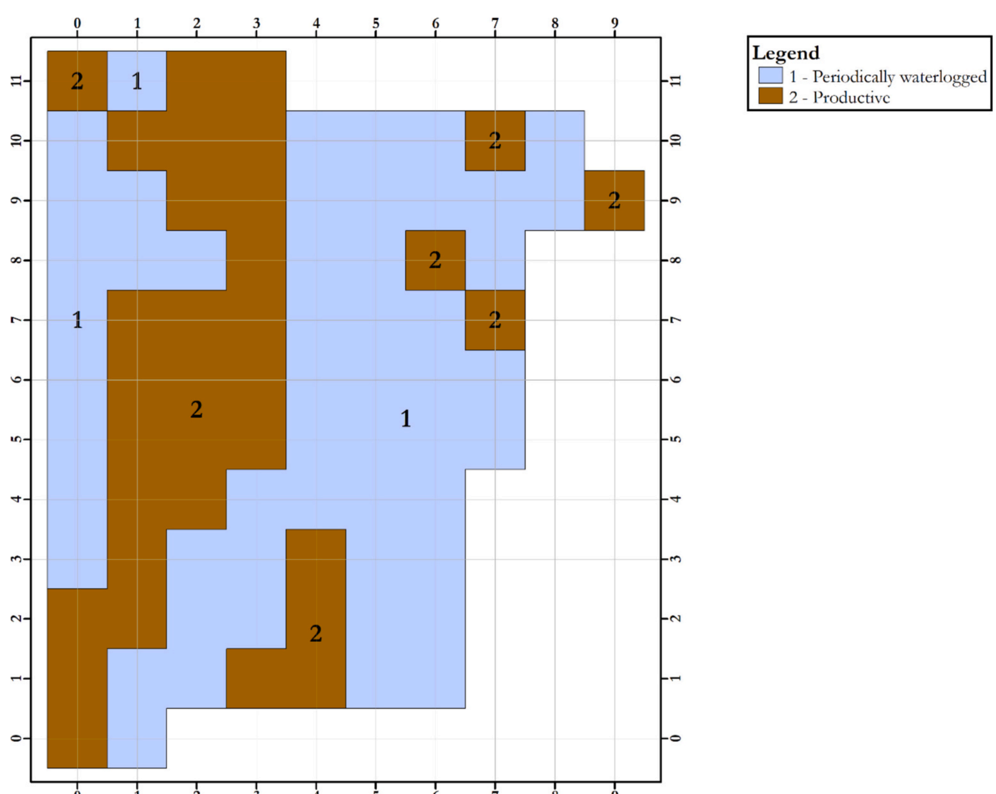

Fig. 19. Indication of raster cells using the cutpoint of 95.47 m for the differentiation of two classes. Class 1 lies below, Class 2 above the elevation of 95.47 m.

designation of precision farming management zones, complementing and refining other available (remotely sensed) information.

Declaration of competing interest

None.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.geodrs.2025.e00927.

Data availability

Data will be made available on request.

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